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Application of Data-Driven Self-Optimizing Control to Reservoir Production Optimization

By

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ABSTRACT

Reservoir waterflooding is one of the cheapest means of producing hydrocarbon from underground formation to the surface. A properly formulated control and optimization strategy will not only solve the process inevitable problems but will also lead the process to optimal operation. Previous optimization studies are model-based, but reservoirs are highly complex, and therefore cannot be described and predicted accurately using models. To counteract the effects of reservoir model/system mismatch, feedback control was suggested to be included in the optimization framework. In this work the principle of self-optimizing control (SOC) is used to derive controlled variable (CV) based on synthetic data. We have previously implemented this methodology on a very small reservoir. The present work extends the implementation to a realistically sized reservoir. In the methodology, the CV is formulated via a single regression step in which a measurement function is used to approximate the gradient of the objective function with respect to control. The developed CV is firstly implemented on a nominal model and then to various uncertain cases. The performance of the method is compared to that of open-loop solution technique, OC (based on optimal control theory) and then to a benchmark case. The developed CV is found to be robust in the presence of uncertainties. In one of the cases considered, the SOC method is found to be better than OC solution procedure by about 24.03%.

Keywords: closed-loop reservoir management, data-driven, optimal control theory, reservoir uncertainty, self-optimizing control.

Introduction

Increase in global population has led to an increase in energy demand; and oil and gas are heavily relied upon to meet this need[1]. As such research interests have sprung over the years on how to efficiently produce these vital resources. One of such activities is in the optimization of reservoir waterflooding processes. Waterflooding is a type of secondary recovery mechanism where water is injected into the reservoir for pressure maintenance and increase in productivity. It is one of the cheapest means of production but is associated with some operational problems such as early water breakthrough and non-uniform sweeping which has to do with heterogeneity in flow determining properties like permeability and porosity. Several remedies were suggested in the past and one of such that is receiving attention is the installation of smart wells. Smart wells, unlike conventional wells are equipped with inflow control devices

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[1] ExxonMobil (2014) "The Outlook for Energy: A View to 2040", http://corporate.exxonmobil.com/en/energy/energy-outlook.

(ICVs) such that measurement and control can be done in real time. Several researches were reported on strategies for optimization and control of smart wells for waterflooding operations[2].

Early works on optimization of waterflooding focused on open-loop control based on reservoir model with the assumption that the model is perfect and captures all reservoir and production behaviours[3]. Unfortunately, reservoir models are too complex with several highly uncertain parameters. Hence, techniques that give open-loop solutions for example, optimal control theory lack robustness to handle uncertainties. Methods to handle reservoir uncertainties have been developed in the past. One of such techniques is robust optimization (RO)[4]. In RO, reservoir realizations are used with the basic assumption that they cover all geological uncertainties. These assumptions are however, unrealistic in practice. Apart from this, 'history matching' is a common procedure used by industries to update reservoir models whenever new measurements become available[5]. Many at times, history-matched models fail to predict reality correctly[6].

For this reason, many authors have opined that waterflooding optimization should be framed in a closed-loop fashion so that measurements can be automatically used to update reservoir models continuously from which prediction of optimal production strategies are made[7]. In the work of Dilib and Jackson [8] for example, a feedback configuration was designed by optimizing feedback control law between measured data and control inputs. The operation performance was found to be insensitive to model uncertainties. Recently, Grema and Cao[9] have developed a simple feedback control strategy based on principle of self-optimizing control (SOC). In SOC, controlled variables (CVs) are selected based on available measurements so that when the CVs are kept constant at their setpoints through feedback control, the operation of the plant is optimal or near optimal[10]. In the work of Grema and Cao[11], measurement data from a nominal model were used to design a CV. The CV was then implemented to different cases of

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[2] A. S. Grema and Y. Cao (2013), "Optimization of Petroleum Reservoir Waterflooding Using Receding Horizon Approach," in *8th IEEE Conference on Industrial Electronics and Applications* held in Melbourne, Australia, , 397–402.

[3] M. Asadollahi and G. Naevdal (2004) "Waterflooding Optimization Using Gradient Based Methods" presented at the SPE/EAGE Reservoir Characterization and Simulation Conference, Abu Dhabi, UAE.

[4] G. van Essen et al., (2009) "Robust Waterflooding Optimization of Multiple Geological Scenarios," *Society of Petroleum Engineers Journal*, 202–210.

[5] B. Foss and J. P. Jensen (2011) "Performance Analysis for Closed-Loop Reservoir Management," *SPE Journal* 16, no. 1: 183–90.

[6] M. Tavassoli, J. N. Carter, and P. R. King (2004), "Errors in History Matching," *SPE Journal* 9, no. 3: 352–61.

[7] D. Jansen, O. H. Bosgra, and P. M. J. Van den Hof (2008), "Model-Based Control of Multiphase Flow in Subsurface Reservoirs," *Journal of Process Control* 18: 846–855, doi:10.1016/j.jprocont.2008.06.011.

[8] F. A. Dilib and M. D. Jackson, (2013) "Closed-Loop Feedback Control for Production Optimization of Intelligent Wells under Uncertainty," *SPE Journal*, 345–57.

[9] A. S. Grema and Y. Cao (2016), "Optimal Feedback Control of Oil Reservoir Waterflooding Processes," *International Journal of Automation and Computing* 13, no. 1: 73–80, doi:10.1007/s11633-015-0909-7.

[10] S. Skogestad, (2000) "Plantwide Control: The Search for the Self-Optimizing Control Structure," *J. Process Control* 10, no. 5: 487–507.

[11] A. S. Grema and Y. Cao (2016), "Optimal Feedback Control of Oil Reservoir Waterflooding Processes," *International Journal of Automation and Computing* 13, no. 1: 73–80, doi:10.1007/s11633-015-0909-7.

uncertainty in a closed-loop. Though the implementation was successful, the CV was formulated based on a very small reservoir (20 m X 20 m X 5 m). Hence, the authenticity of the method cannot be ascertained when it comes to real implementation. In this work, the methodology reported by Grema and Cao [12] was extended to be derived and implemented based on a realistic reservoir size. The derived CV was then implemented on cases with different degrees of uncertainty.

Methodology

The approach outlined in Grema and Cao [13] is strictly followed here which is outlined below.

SOC for Waterflooding Operation

A reservoir model is written in a discretised form as follows [14]

$$\boldsymbol{g}(\boldsymbol{u}^k, \boldsymbol{x}^{k+1}, \boldsymbol{x}^k, \boldsymbol{\varphi}) = \mathbf{0} \tag{1}$$

In Equation (1), $\boldsymbol{u}^k$, is a vector of controls at time k whose change will affect a given control objective through state variables, $\boldsymbol{x}^{k+1}$ while $\boldsymbol{\varphi}$ is a parameter vector. The state will also influence the outputs, $\mathbf{y}^{\mathrm{k+1}}$ according to

$$\boldsymbol{h}(\boldsymbol{u}^k, \boldsymbol{x}^k, \boldsymbol{y}^k) = \mathbf{0} \tag{2}$$

For such system, the objective to be minimised can be represented by [15]

$$J = \sum_{k=1}^{N} J^k(\boldsymbol{u}^k, \boldsymbol{y}^k, \boldsymbol{d}^k) \tag{3}$$

Where the summation is over a total time N and the $\boldsymbol{d}$ is a vector of uncertainties and disturbances. The data-driven SOC procedure according to Grema and Cao [16] starts by designing a CV offline and then implementing the CV online. In order to formulate the CV offline, a control sequence is first defined which is used to solve the reservoir model from which a solution sequence of states and measurements are obtained. The reservoir model is solved again with a perturbed control sequence to generate measurement data. This procedure is repeated for a predefined number with the measurements being stored. It has been shown in Grema and Cao [17] that the CV as a function of measurements can be expressed in

$$J_{i+1} - J_i = \sum_{j=1}^{n_u} \sum_{k=n+1}^{N} C\big(\boldsymbol{\theta}_j, \boldsymbol{y}_i^k, \boldsymbol{y}_i^{k-1}, \dots \boldsymbol{y}_i^{k-n}, u_{i,j}^k\big)\big(u_{i+1,j}^k - u_{i,j}^k\big) \tag{4}$$

Where $\boldsymbol{\theta}_j$ are parameters to be determined through regression for an input channel j and n_u is the total number of inputs. The CV function in Equation (4) also contains the input $u_{i,j}^k$, the feedback control therefore is obtained directly by setting $C = 0$.

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[12] Ibid.
[13] Ibid.
[14] Ibid.
[15] Ibid.
[16] Ibid.
[17] Ibid.

Case Studies
The reservoir was simulated using MRST [18] with 30 x3 x 1 cells. Having size of 2250 m x 225 m x 10 m, each cell is therefore 75 m x 75 m x 10 m. Two wells are drilled vertically (injection and production wells) which are located at the two ends of the reservoir. The reservoir is a two-phase system of oil and water with homogenous rock and fluid properties. It is characterised with a permeability of 400 mD and a porosity of 0.3. Other properties used are as given in Table 1.

The above reservoir configuration was taken as a nominal model (Case I) which is used to design the proposed feedback control law. Three other cases are derived from the nominal model by changing one or more properties. In Case II for example, uncertainty in permeability is studied. In this case, the reservoir was assumed to have five vertical layers of different permeability. The permeability is log-normally distributed with mean values of 200 mD, 500 mD, 350 mD, 700 mD and 250 mD from top to bottom[19]. For Case III, uncertainty in fluid properties is considered, typically, the shape of oil-water relative permeability curves or phase relative permeability exponents. The nominal value for this parameter for both oil and water is taken as 2.0 while the actual value is 1.5. A little more uncertainty is considered in Case IV. Typically, uncertainties in reservoir size, geometry and structure are considered[20]. The reservoir is claimed to be of 225 m x 22.5 m x 1 m modelled with a corner point gridding system with a wavy top and bottom. The reservoir also has a fault of 0.12 m [21].

Table 1: Properties for Nominal Reservoir Model

Property	**Value**	**Unit**
Porosity	0.3	-
Oil viscosity	5	cp
Water viscosity	1	cp
Oil density	859	Kg/m^3
Water density	1014	Kg/m^3
Oil Corey exponent	2	-
Water Corey exponent	2	-

Data Gathering
The nominal model described above is used to collect simulated data for determining CV coefficients through regression. The two-well system (single injection and production wells) are controlled by the total rate of production (for the production well) and rate of injection (for the injection well), that is, two manipulated variables (MVs). However, a voidage replacement assumption was employed, which means total amount of injection must equal total production at all time steps. With this assumption, the number of MVs is reduced to two. From the

[18] SINTEF, "MRST Documentation Page," Online, (2014), http://www.sintef.no/Projectweb/MRST/.
[19] A. S. Grema and Y. Cao (2016), "Optimal Feedback Control of Oil Reservoir Waterflooding Processes," *International Journal of Automation and Computing* 13, no. 1: 73–80, doi:10.1007/s11633-015-0909-7.
[20] Ibid.
[21] B. Foss and J. P. Jensen (2011) "Performance Analysis for Closed-Loop Reservoir Management," *SPE Journal* 16, no. 1: 183–90.

simulation results, oil and water production rate are recorded as well as water injection rate which is the MV. The measurement vector can therefore be represented as

$$\boldsymbol{y} = [y_o \; y_w \; u_w]^T \tag{5}$$

Where y_o and y_w are oil and water production rates while u_w is water injection rate. The objective function, which is net present value (NPV) see Grema (2014)[22] is also computed from these measurements. This is written as

$$J^k = \left\{ \frac{\sum_{j=1}^{N_{prod}} \left[r_o\left(y_{o,j}\right)^k - r_{wp}\left(y_{w,j}\right)^k \right] - \sum_{i=1}^{N_{inj}} r_{wi}\left(u_{w,i}\right)^k}{(1+b)^{\frac{t^k}{\tau}}} \right\} \Delta t^k \tag{6}$$

Where r_{wi} is water injection cost, r_{wp} is water production cost, r_o is oil production unit income, b is discounting factor, τ is reference time for discounting and t^k is the time at k^{th} step. An oil price of $100/bbl was used while water injection and production costs were both fixed at $10/bbl. A zero-discounting factor, b was used.

Here 200 solution trajectories were obtained using a time-step size of two days. Therefore, regression was performed using a 200 x 365 data matrix to obtain the required CV.

Regression and Feedback Control Formulation

Using the measurement set in Equation (5), a linear time-series model of the form [23]

$$C = \theta_1 y_{i,o}^k + \theta_2 y_{i,w}^k + \theta_3 y_{i,o}^{k-1} + \theta_4 y_{i,w}^{k-1} + \cdots + \theta_{2(n+1)} y_{i,w}^{k-n} + \theta_{2(n+1)+1} u_w^k \tag{7}$$

was chosen for the CV function with two past histories ($n = 2$). The total number of coefficients to be determined is therefore $2(n+1)+1 = 7$.

Regressions were performed by minimizing the square of the residual given by [24]

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^{N} \left((J_{i+1} - J_i) - q \right)^2 \tag{8}$$

Where q represents the right-hand side of Equation (4).

A feedback control law can be obtained from Equation (7) by setting it to zero (NCO) which can be written as ($n = 2$) [25]

$$u_{w,fb}^k = -\theta_7^{-1} [\theta_1 y_o^k + \theta_2 y_w^k + \theta_3 y_o^{k-1} + \theta_4 y_w^{k-1} + \theta_5 y_o^{k-2} + \theta_6 y_w^{k-2}] \tag{9}$$

After the CV was designed, it was first implemented on the nominal case and then to the other three cases with different degrees of uncertainty. These were compared to the open-loop control

[22] A. S. Grema (2014), "Optimization of Reservoir Waterflooding" PhD thesis, Cranfield University, Cranfield, U.K.

[23] A. S. Grema and Y. Cao (2016), "Optimal Feedback Control of Oil Reservoir Waterflooding Processes" Int. J. Autom. Comput. 13, 73–80. doi:10.1007/s11633-015-0909-7

[24] Ibid.

[25] Ibid.

solutions, OC and to the BM where all the reservoir properties were assumed to be known a priori.

To ascertain the capability of the designed CV, two performance indices were used. A loss which compares the performance of the SOC approach and that of an open-loop solution (OC) to a benchmark (BM) is computed via

$$Loss = \frac{J_{BM} - J_{SOC/OC}}{J_{BM}} \times 100\% \tag{10}$$

Furthermore, superiority of SOC performance over OC was demonstrated through gain which is

$$Gain = \frac{J_{SOC} - J_{OC}}{J_{SOC}} \times 100\% \tag{11}$$

Results and Discussions

CV and Regression

A control law obtained from regression using the nominal model is given below

$$u_{w,fb}^{k} = -(-4.0243 \times 10^{7})^{-1}[0.0000y_{o}^{k} + 1.7216y_{w}^{k} + 4.0256y_{o}^{k-1} + 0.0000y_{w}^{k-1} + 0.0017y_{o}^{k-2} + 2.3041y_{w}^{k-2}] \times 10^{7} \tag{12}$$

It can be seen from Equation (12) that current measurement of oil production rate and first history of water production rate are not relevant in the feedback control expression. The R^2-value is 0.9856, so the linear model chosen is sufficient to represent the CV.

Case I: Nominal Case

The feedback control law in Equation (12) was implemented on the nominal model, the performance of which was compared to that of OC approach. The loss incurred as a result of the feedback implementation is only 0.11%.

The CV was well maintained around zero, hence the reason for the good performance of the SOC approach. The injection settings found was almost like those of OC counterparts. As is shown in Fig. 1, the SOC's injection rate was initially lagging OC's, although it was on the increase till it exceeded the OC strategy. To put the process on the optimal path, the injection rate was forced to decline and maintained at near constant. This injection pattern has led to production profiles that are like those obtained using the true optimal solutions (Fig. 1). In summary, the performance of the two strategies is given in Table 2.

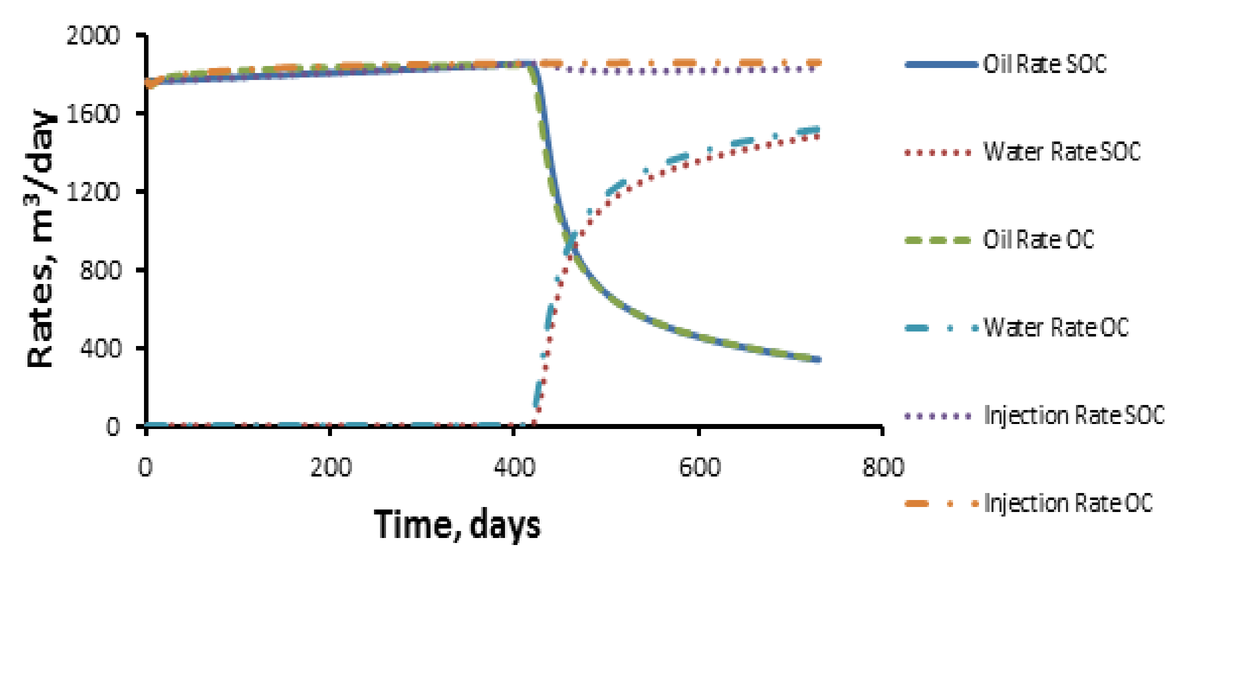

Figure 1: Rates Profiles for Case I

Table 2: OC and SOC Performance Comparison for Case I

Strategy	Total Oil (m^3)	Total Water (m^3)	Time of Water Break-Through (days)	NPV ($)
SOC	951,305.40	372,821.70	408	492,636,353.90
OC	954,458.90	386,835.30	404	492,654,987.39

Case II: Uncertainty in Permeability

When uncertainty in permeability was introduced into the system, the gain is 1.03% compared to OC approach. The losses based on BM scenario are 0.028% and 1.061% for SOC and OC respectively.

This amazing performance by SOC is attributed to its injection settings whose profile is like that of BM approach. Both injection profiles can be seen to average at 2200 m^3/day; while in the case of OC, the average is about 1800 m^3/day (Fig. 2). The SOC injection rates have similar flooding effect to that of BM case which can be observed from the production profiles of oil and water in Fig. 3. The injection rates of OC however, have produced lower amounts of oil and water with reduced NPV; the results of which are summarised in Table 3. Although, OC was seen to have a late water break-through compared to other two cases, this has not improved its relative performance in anyway.

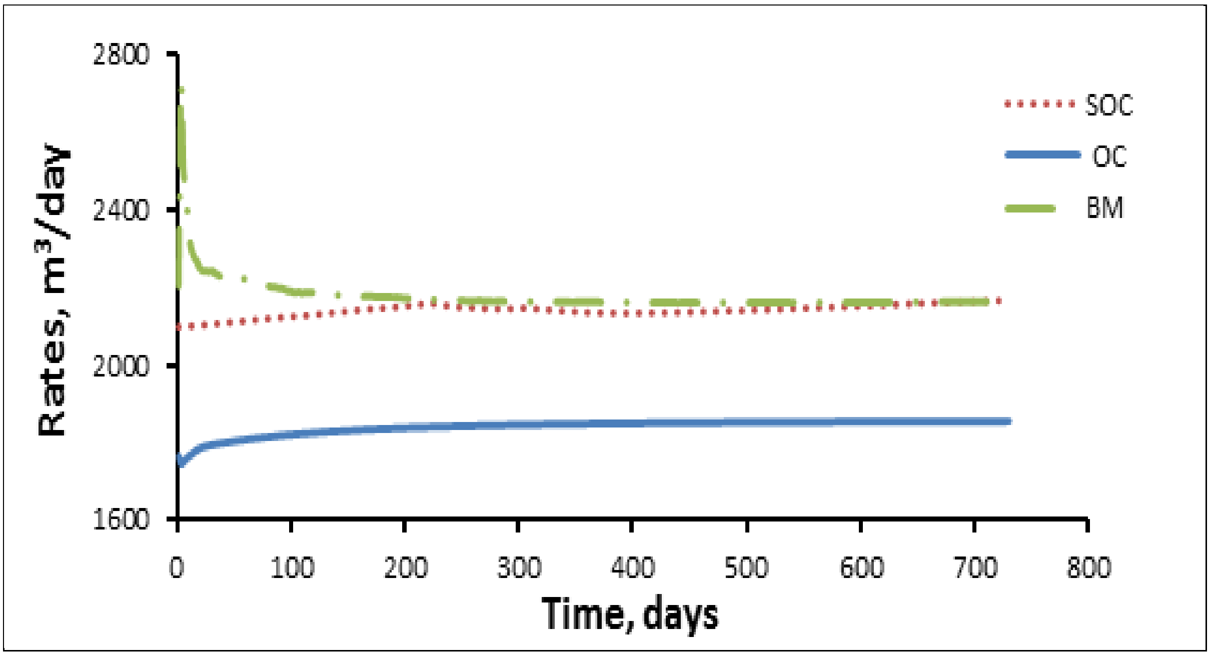

Figure 2: Injection Rates for Case II

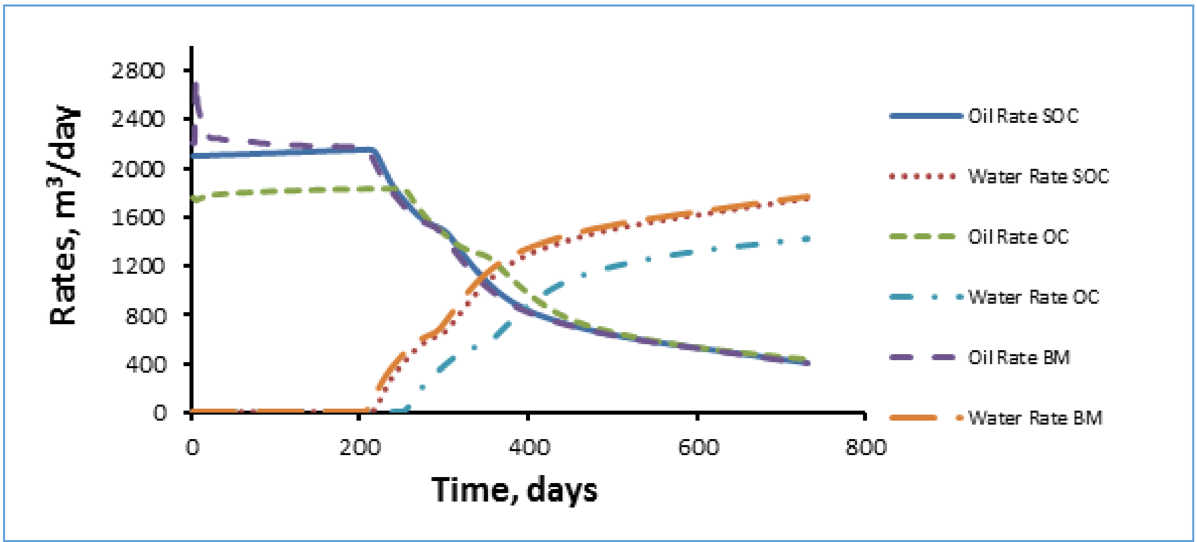

Figure 3: Production Profiles for Case II

Table 3: OC and SOC Performance Comparison for Case II

Strategy	Total Oil (m^3)	Total Water (m^3)	Time of Water Break-Through (days)	NPV ($)
SOC	905,909.77	654,407.30	210	431,526,889.97
OC	859,567.48	481,726.65	246	427,065,786.20
BM	910,892.28	675,827.96	200	431,646,157.23

Case III: Uncertainty in Phase Relative Permeability Exponents

The nominal relative permeability exponent used is 2.0 as stated earlier. It was assumed that the actual value is 1.5. The losses recorded by SOC and OC approaches for this case of uncertainty are 0.39% and 1.66% respectively. A gain of 1.27% in NPV was obtained in favour of SOC.

Even though there is a wide separation between optimal injection rates found by SOC and BM, the trends are almost similar (Fig. 4). Furthermore, with these injection settings favourable production profiles were obtained by SOC approach that led to a significant gain in comparison to OC. As can be seen from Fig. 5, a broad oil production plateau with intermediate water production rates were realised through the former approach, a reason for a better NPV that is comparable to that obtained with an assumption of perfect reservoir knowledge. These results are highlighted in Table 4.

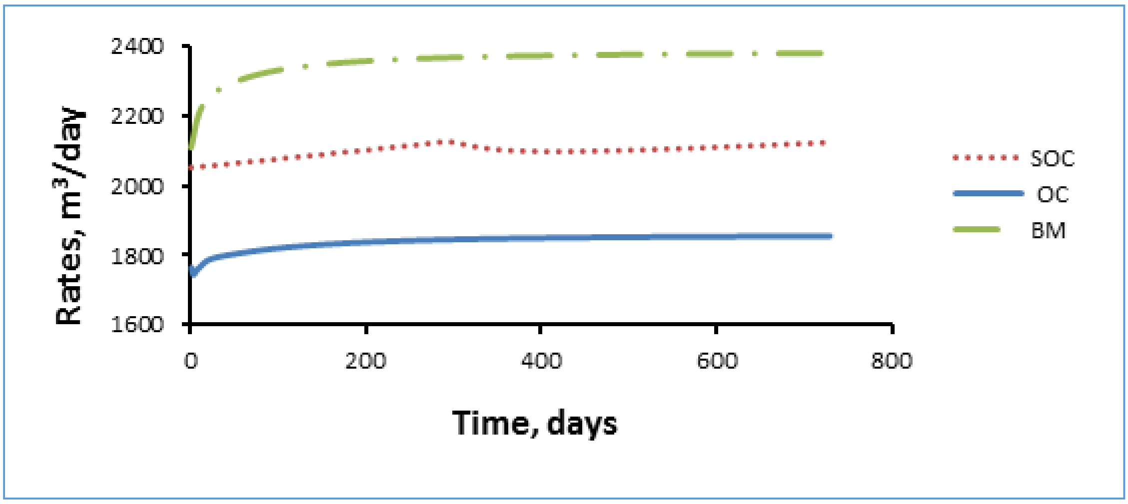

Figure 4: Injection Rates for Case III

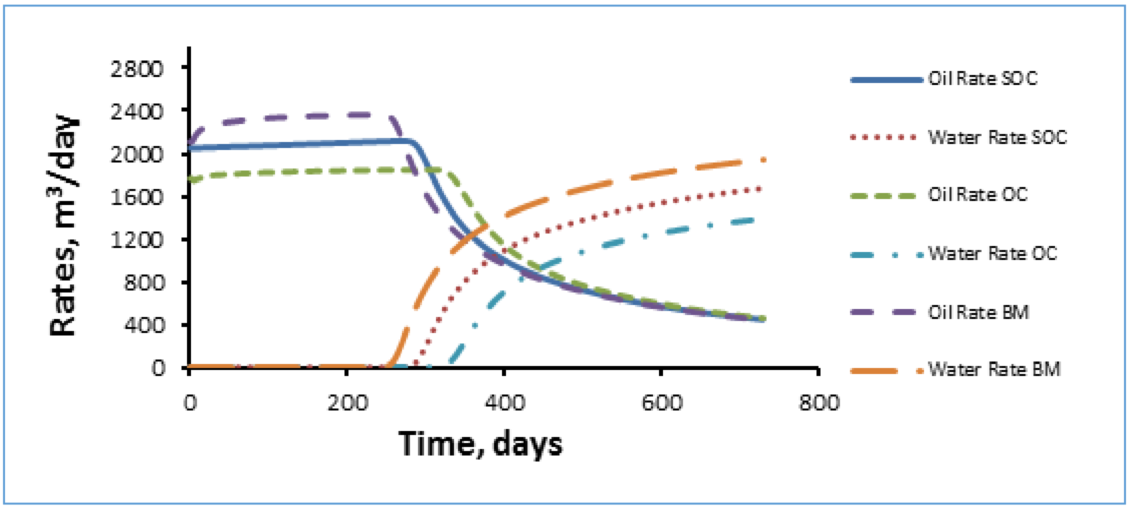

Figure 5: Production Rates for Case III

Table 4: OC and SOC Performance Comparison for Case III

Strategy	Total Oil (m^3)	Total Water (m^3)	Time of Water Break-Through (days)	NPV ($)
SOC	974,580.53	554,721.52	266	483,011,497.29
OC	931,458.34	409,835.79	246	476,865,932.82
BM	1,011,441	705,059.45	242	484,924,572.10

Case IV: Uncertainty in Reservoir Size, Geometry, and Structure
Here the truth reservoir size is 2250 m x 250 m x 2 m (smaller in size to the nominal model) but modelled with grid cells of 30 x 3 x 1 using corner point gridding system. The reservoir has a fault of 0.3 m. Open-loop optimal control sequence was directly obtained from this reservoir which serves as the BM case. Similar comparisons performed in Cases II and III were also carried out here by applying the two approaches of SOC and OC (based on nominal model) on this truth reservoir. Losses based on BM are 0.54% and 24.44% for SOC and OC respectively. The gain in implementing the feedback strategy is 24.03% as compared to OC. This demonstrates the robustness of the developed feedback strategy in counteracting uncertainty.

Despite the high degree of uncertainty considered in this case, the injection profile found through the application of SOC methodology mimics the BM scenario. The OC injection rates which are near 1800 m^3/day are completely out of the optimal range for this reservoir system (Fig. 6). This can easily be proven from oil and water production profiles shown in Fig. 7. The OC injection setting is very high for this size of reservoir, a reason for accelerated oil production with a smaller plateau period and early water break-through characterised by very high flow rates. On the other hand, both oil and water production profiles found by SOC approach are similar to the BM scenario despite the presence of uncertainty. Table 5 gives a summary of the results obtained.

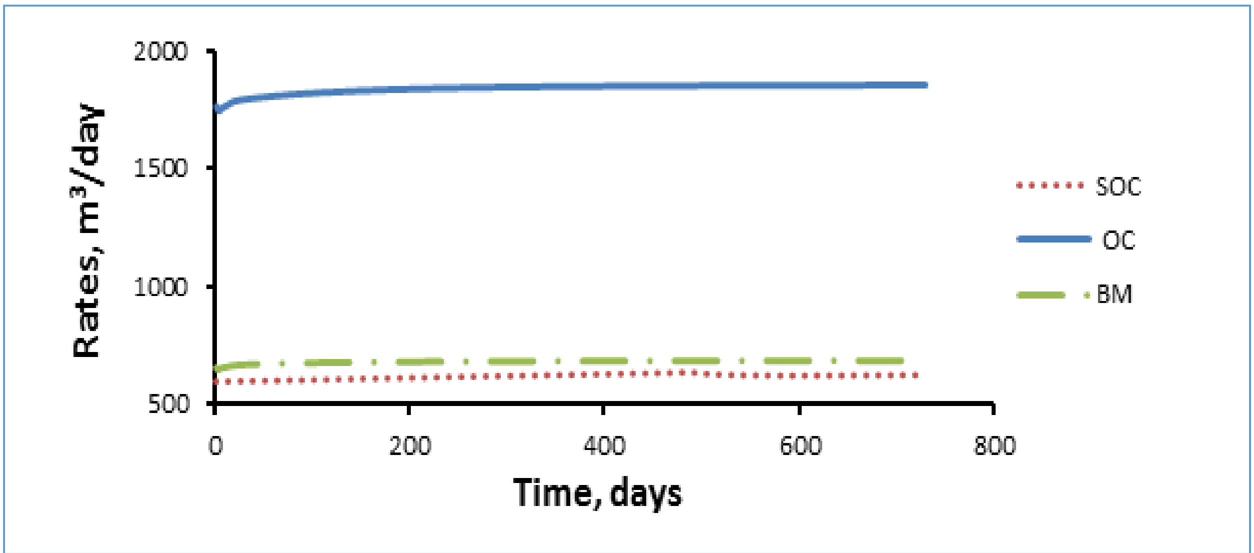

Figure 6: Injection Rates for Case IV

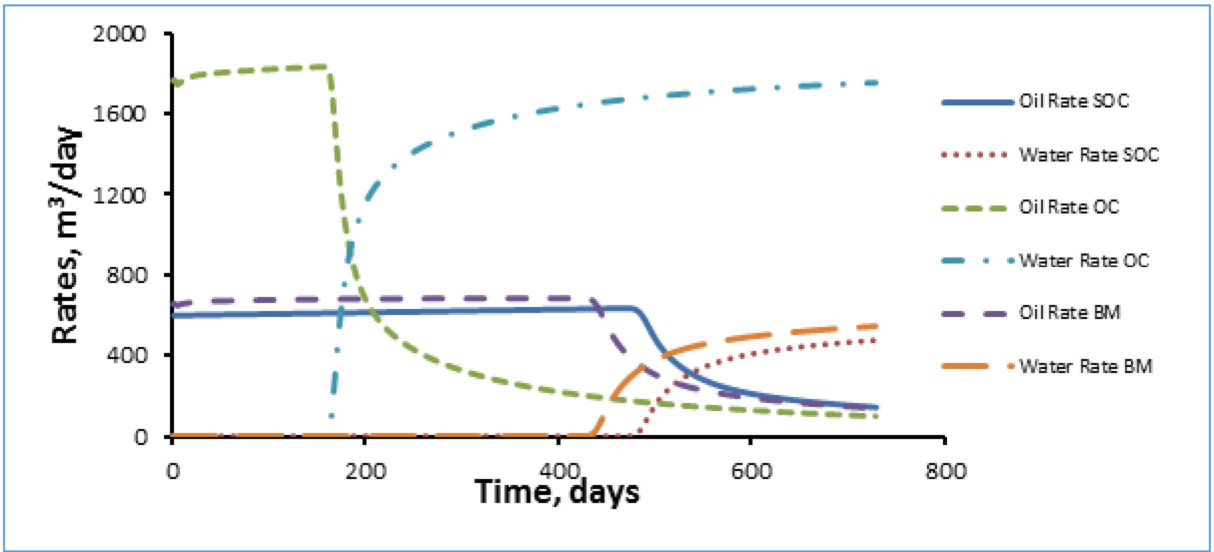

Figure 7: Production Rates for Case IV

Table 5: OC and SOC Performance Comparison for Case IV

Strategy	Total Oil (m^3)	Total Water (m^3)	Time of Water Break-Through (days)	NPV ($)
SOC	360,140.80	92,219.57	237	192,693,715.20
OC	453,370.75	884,394.02	156	146,392,742.65
BM	370,103.01	128,620.17	422	193,742,723.85

Conclusion and Recommendations

A controlled variable design was performed for a realistic reservoir through data-driven self-optimizing control. In the method, a nominal reservoir model was used to sample measurements including oil and water production rates from which a linear CV function was constructed via regression. The obtained CV was first implemented on the nominal model and then on some uncertain cases. The performance of the CV was compared to open-loop control and to a benchmark.

The data sampling procedure adopted has led to a satisfactory goodness of fit. When the CV was implemented on the nominal model, a control trajectory similar to truth optimal control based on optimal control theory was obtained, which confirms the accuracy of the developed CV. Furthermore, the CV has shown to be robust in the presence of uncertainties in some reservoir and fluid properties such as permeability, Corey exponents, reservoir geometry and size. The relative performance of the SOC method (in comparison to an open-loop solution) increases with increase in severity of uncertainty. For instance, when uncertainty in permeability alone was considered, a gain in NPV by SOC is 1.27%. The gain is 24.03% when uncertainties in reservoir size, geometry and structure were considered. This result agrees with the findings of Grema and Cao [26].

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[26] Ibid.